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Modeling of Photosynthesis in Soybean Crops Using Artificial Neural Networks

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ABSTRACT

Important to NASA's Advanced Life Support program is the development of an autonomous, dynamic, self-contained bioregenerative life support system for future, long duration spacecraft and space stations to provide fresh food, air, water and to recycle waste products. These systems will rely on plants to rejuvenate the air and produce food through the process of photosynthesis and purify water through the process of transpiration. An intelligent, autonomous, reliable, and robust control system must be developed and applied to dynamically manage, control and optimize plant-based life support functions to allow the efficient growth of plants, providing the maximum amount of life essentials while using minimal resources. System identification and modeling of plant growth behavior must first be developed to characterize plant growth functions in order to develop an efficient control system.

We have developed an artificial neural network model to characterize the photosynthesis process of soybean crops under various environmental conditions. It is a 2-layer feedforward neural network architecture which inputs the crop type, age, and the environmental conditions of the crop canopy: carbon dioxide level, light intensity, temperature, and relative humidity and outputs the predicted net photosynthesis or assimilation rate produced under these conditions. The neural network model was trained from controlled environment soybean crop experiments conducted at Rutgers University in New Brunswick, New Jersey where dynamic plant responses over a range of environmental conditions were collected. This paper will discuss in more detail the motivation for developing the crop model, the neural network model and performance and the crop experiments and data collected by Rutgers University.

INTRODUCTION

Future spacecraft and space stations for long-term space exploration and habitation will require an autonomous, dynamic, self-contained bioregenerative life support system to provide fresh food, air, and water and to recycle waste products. One of the objectives of NASA's Advanced Life Support program is to develop such a system that will achieve safe, reliable, and efficient support of human crews.[1] In order to provide a significant degree of self-sufficiency to allow the crew members to conduct productive research and exploration of space, future bioregenerative life support systems will rely on plants to perform several functions. Through the process of photosynthesis or assimilation, plants remove carbon dioxide from the atmosphere and produce oxygen while incorporating carbon into biomass (food). Fresh water is released via the process of transpiration. As shown in Figure 1, a multi-crop growth chamber can be directly connected to crew areas to dynamically rejuvenate air, purify water, and produce food and reutilize waste. Understanding and optimally controlling these dynamic functions associated with assimilation, transpiration, biomass accumulation and allocation, as well as the demands for resources (resources recovered from wastes) is essential to designing and managing long-term operation of bioregenerative life support systems.[1,2]

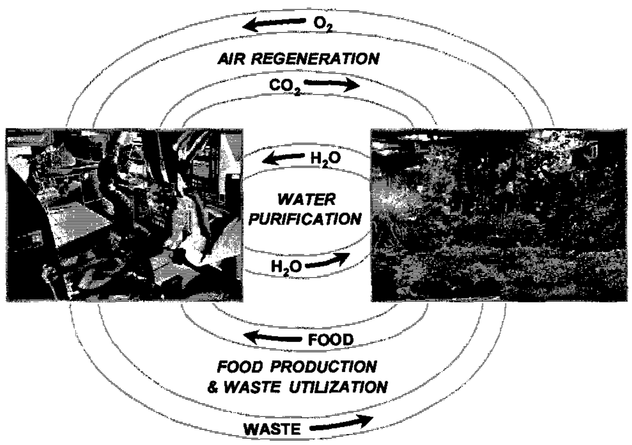


Figure 1: Autonomous and dynamic bioregenerative life support system.

An intelligent, autonomous, dynamic, reliable, and robust control system must be developed and applied to manage, control and optimize plant-based life support functions.[2] This will allow efficient growth of plants to provide the maximum amount of life essentials of air, water, and food to a human crew using the minimal amount of limited resources available in space. Since the crew can be working, exercising, sleeping, as shown on the left in Figure 1, and therefore dynamic, the control system needed to support them also needs to be dynamic and be able to adapt to their changing needs. Traditional control systems using PID (Proportional, Integral, Derivative) control methods are limited and will not be able to efficiently and fully adapt to the life support needs of a crew and their changing environment without heavy buffering. Production of plants in one or more controlled environments and their dynamic interaction with crew areas must be carefully monitored and controlled with limited or no buffering.

We are developing an artificial neural network control system for use in bioregenerative life support systems. The neural network system will examine the real-time needs of a crew and then control the rates of various plant physiological processes accordingly, by manipulating the environment. As shown in the bottom of Figure 2, the neural network control system will determine how to optimally grow the plants with a minimum amount of energy (number of lights, photoperiod, nutrients, etc.) and with the available resources (CO_2, water, etc.) to produce the necessary amount of oxygen, water, and food for the crew members as required, specified, or determined by life support needs.

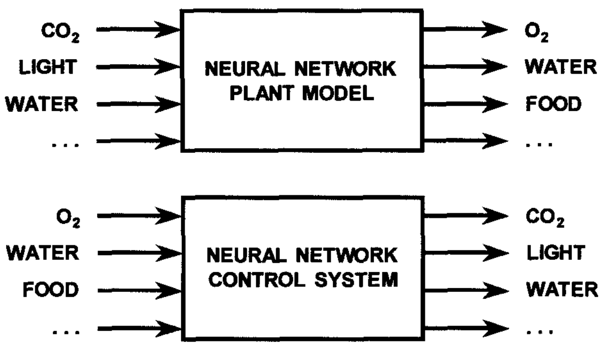


Figure 2: Approach to the development of an artificial neural network plant model and control system.

To develop an efficient control system using artificial neural networks for plant-based life support functions, system identification and modeling of plant growth behavior must first be accomplished since these functions are dependent on plant performance.[2] Current physiology-based, mathematical crop models are very limited. They usually only model a single process such as photosynthesis or transpiration (and not both) for a specific plant at a specific stage of growth under a specific growing condition which is specific to a particular growth chamber. Furthermore, the mathematical equations governing some of these models, since they are low-order and rather simplified, make certain assumptions and do not fully characterize all the multivariable interactions. As shown on the right of Figure 1, a multicrop growth chamber with a variety of different plants which are all growing at different stages will probably be used as part of a bioregenerative life support system. Certainly, a more complete, complex, and system/chamber independent plant model needs to be developed to characterize the behavior of plants inside a multicrop chamber. Thus, we are implementing neural network models characterizing plant growth functions first (top of Figure 2). These plant growth (physiology) models will provide an understanding of plant behavior necessary for the development of a life support system model. They will be able to better interpolate between various environmental conditions and parameters and be able to simulate short-term (less than a day) and long-term (plant life cycle) responses and performance of various plants. These models will also serve as tools to emulate and provide sufficient amounts of data over an adequately wider range of conditions and performance for development and training of the neural network control system.

As shown in Figure 2, the inputs to the neural network models are the environmental conditions and parameters and the outputs are the important products (food, air, and water) needed for a crew produced as a simulated response to the inputs. It should be noted that the outputs of the plant model are the inputs to the control system and likewise, the outputs of the control system are inputs to the plant model. Thus, the control system is an inverse of the plant model. Using neural networks, this type of implementation is not difficult to develop.

ARTIFICIAL NEURAL NETWORK CROP MODEL

Inspired by biological systems, artificial neural networks are highly parallel data processing systems and are particularly suited to "learn" ill-defined or fuzzy input-output relationships and to perform adaptive interpolations.[3] With their capability to learn from experience rather than be cast in preset rules, neural networks are capable of easily performing many tasks that conventional regression techniques and traditional artificial intelligence systems find difficult or impossible to solve. Artificial neural networks with their ability to learn and approximate arbitrary nonlinear input-output relationships from a collection of examples are very suitable for dynamic modeling, identification, and characterizing plant-based life support processes. They can be trained to simulate complex, nonlinear, multimodal, multivariable functions that will be able to better interpolate between various conditions and parameters. Thus, artificial neural networks may be ideally suited as an intelligent computational methodology that would assimilate a variety of environmental inputs and parameters and efficiently and autonomously control and optimize the growth of crop plants.

The potential benefits of neural networks extend beyond the high computation rates provided by massive parallelism. They provide a greater degree of fault tolerance toward variations with input signals.[4] Neural network learning algorithms adapt their synaptic connection weights in time to improve performance based on the current results. Adaptation provides a degree of robustness by compensating for minor variations in the inputs as well as in the characteristics of the neurons. Traditional statistical techniques are not adaptive, typically processing all training data simultaneously before being given new data. Neural network classifiers are also non-parametric and make weaker assumptions concerning the shapes of underlying distributions than traditional statistical classifiers.[4] They may thus prove to be more robust and realistic when distributions are generated by nonlinear processes and are strongly non-Gaussian.[4]

A neural network is characterized by its pattern of connections between the neurons (architecture), its neuron function, and its method of determining the weights on the connections (training or learning algorithm). In general, the architecture can be defined as an interconnection (network) of neurons such that neuron outputs are connected, through synaptic weights, to other neurons. The synaptic weights represent information being used by the network to solve a problem.

The artificial neural network developed to model plant growth is shown in Figure 3. It uses a traditional feedforward neural network structure. In a feedforward architecture, all the inputs are fed to a layer of neurons through synaptic weights (represented by the connecting lines in Figure 3) in such a way that each input is fed to all of the neurons. Similarly each neuron in this layer is connected to each neuron of the next layer through synaptic weights. The layer may be similarly connected to another layer which may be the final layer giving the resulting outputs and thus called the output layer. The intermediate layers between the inputs and the output layer are termed hidden layers. This type of architecture is a feedforward network because of the forward flow of signals. The neural network plant model is a 2-layer network with a single hidden layer and an output layer.

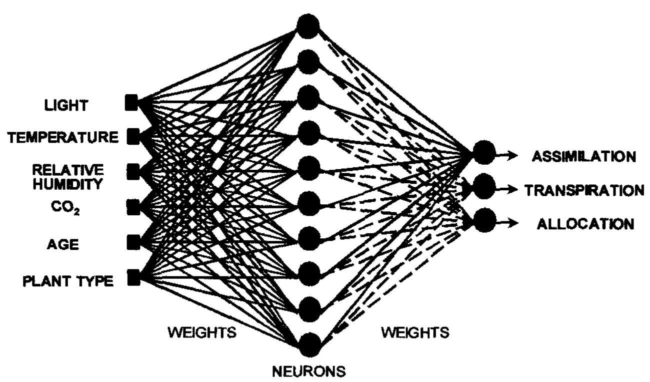


Figure 3: Artificial neural network plant model.

The neural network uses 10 neurons (represented by circles in Figure 3) in the hidden layer and 3 neurons on the output layer. The neuron is a simple processing node with synaptic input connections and a single output. The basic operation of an artificial neuron involves summing its weighted input signals (representing synaptic strength) and applying a nonlinear output, or activation function. The summed value determines the activation level of the neuron. The activation function used in our network is a bipolar sigmoidal function and thus, the output of a neuron is a value between -1 and 1. This means that the external inputs to the network need to be scaled to a value within this range of -1 and 1 and the results of the output neuron must also be scaled or interpreted appropriately to the proper range.

The inputs to the neural network plant model are the environmental conditions of the chamber or crop canopy: carbon dioxide level, light intensity, temperature, and relative humidity as well as the age of the crop and the crop type, a total of 6 inputs as shown in Figure 3. The neural network model simulates the plant response to these conditions and outputs the net photosynthesis or assimilation rate of the plant. Although our current plant model only models the assimilation process, it is shown in Figure 3 with dotted lines/connections that the neural network can easily be expanded to also model the plant transpiration and allocation functions.

Four crop processes have been identified as critical to plant-based life support systems operation.[2,5] Transpiration is the process of water production by the plant, taking up water from the root zone and evaporating pure water from the leaves. Assimilation is the process of CO_2 removal from the gaseous atmosphere and the concomitant release of O_2 by the plant. Allocation is the distribution of photosynthate fixed during assimilation to the various plant parts. High yield efficiencies are the result of allocation of significant biomass to the harvested food product and not the roots, shoots or leaves. Nutrient and water demand set the requirements for recovery of these crop production inputs. Taken together these key processes result in a complete plant-based life support system package which can be highly reliable and controllable.

Our current neural network model was designed only for the net photosynthesis process of a crop, as a start, which is a combination of the assimilation and respiration processes. This process is important and is driven by the application of photosynthetic photon flux in the presence of carbon dioxide and appropriate temperature and nutrition. Since plants convert carbon dioxide to plant biomass and oxygen through the photosynthesis process, modeling and controlling this process will facilitate the design of crop-based systems for both air management and food production. A crew member generates about one kilogram of carbon dioxide per day which can be converted through crop assimilation.[5] Furthermore, assimilation is a complex, nonlinear, dynamic, and multivariable plant process where not all relationships between various environmental conditions and input sensor parameters are well defined. Modeling this process will demonstrate the capabilities of artificial neural networks.

CROP GROWTH EXPERIMENT AND DATA

While controlled environment crop production monitoring systems can generate huge amounts of data regarding environmental conditions and the maintenance of set-points, typical controlled environment production provide few data regarding the dynamics and control of the plant-based life support functions. It is the response of plant behavior over ranges of environmental conditions that enable prediction and lead to stable, autonomous control systems. Unique data regarding the control and response of critical life support related plant processes must be generated and provided to develop such a system.

In a collaboration with Rutgers University in New Brunswick, New Jersey, part of the New Jersey - NASA Specialized Center of Research and Training (NJ-NSCORT) program, controlled environment soybean crop experiments were conducted to collect dynamic plant responses over a range of environmental conditions to train the neural network model. They have designed and constructed four acrylic plant growth chambers housed in an environmentally controlled walk-in chamber, shown in Figure 4, capable of monitoring canopy net photosynthetic rates, dark respiration, and water vapor flux.[6] In addition, the environment inside the closed and controlled chamber can be monitored and set at various levels.

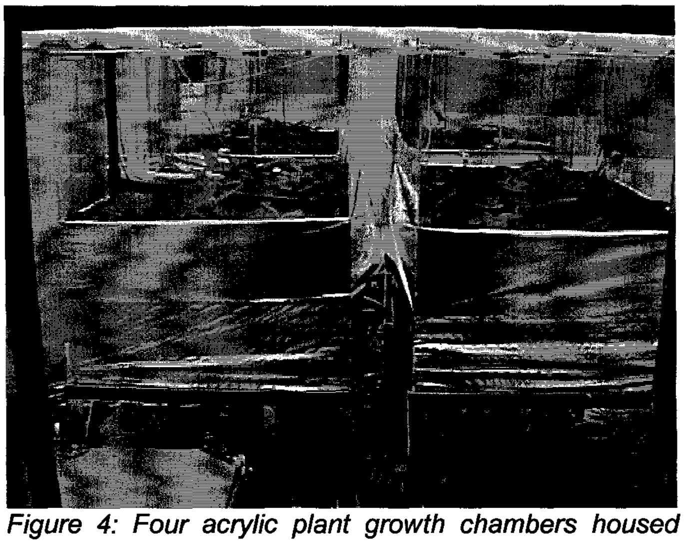


Figure 4: Four acrylic plant growth chambers housed inside an environmentally controlled walk-in chamber designed and constructed to monitor canopy gas-exchange at Rutgers University.

The design of the crop experiment involves setting the environmental conditions inside the chamber to different levels and measuring the net photosynthetic response of the plant. The short-term experiment will last 48 hours and will be conducted during the vegetative stage of crop growth. The experiment will be a factorial design with two levels of atmospheric CO_2 concentrations at 400 and 1000 vpm, three irradiances at 625 and 425 μmol/m^2/s and at no light, and three air temperatures at 22, 26, and 30°C as shown in Figure 5. The environmental conditions for each combination of these settings will be maintained for 2-hour period to allow time for reaching a steady-state condition. Soybean crops (cv. Hoyt) were chosen by Rutgers University for this experiment. Figure 6 shows the soybean crops during the short-term experiment.

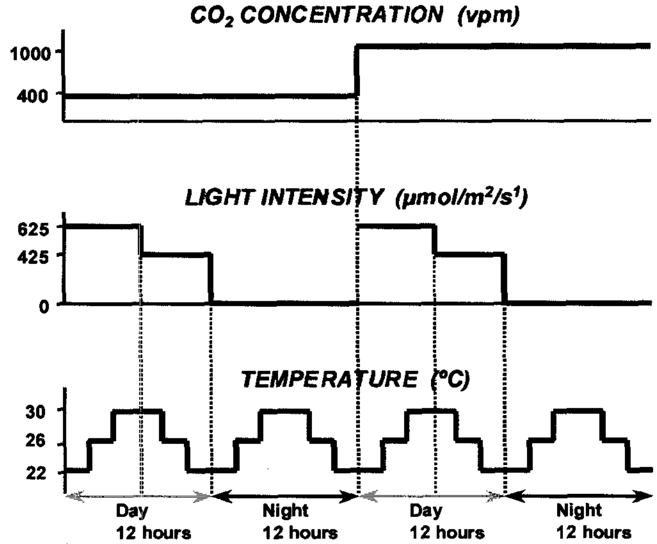


Figure 5: Experimental design with varying environmental conditions.

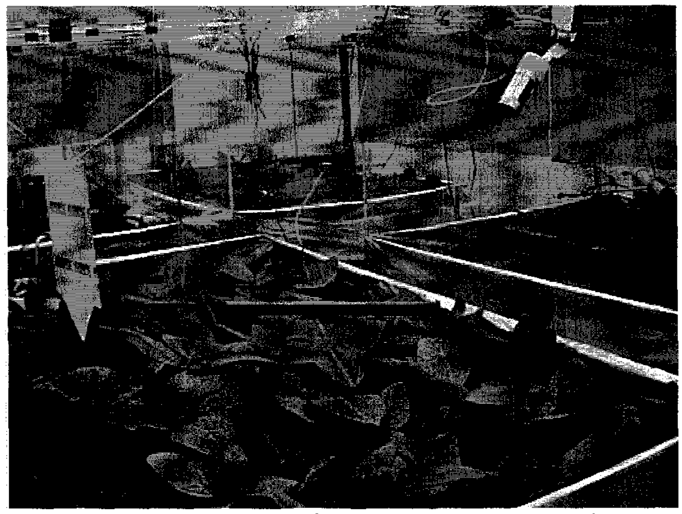
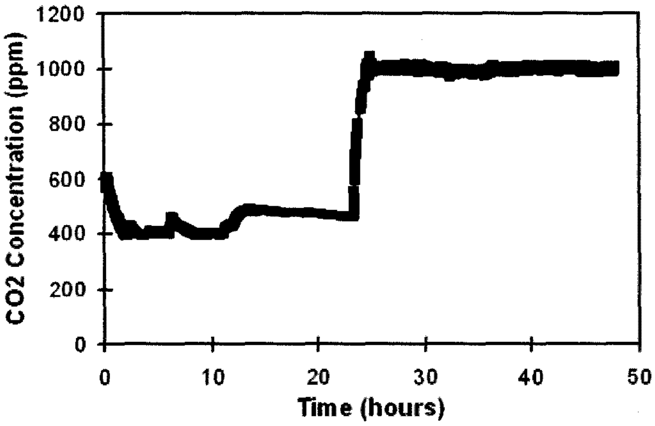
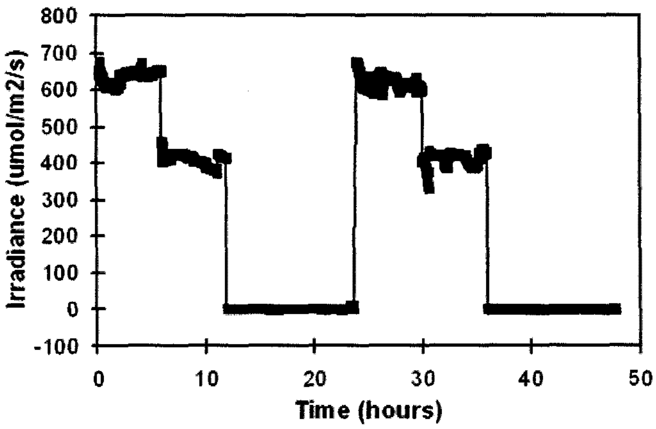


Figure 6: Soybean crops for the short-term experiments.

The environment conditions: CO_2 concentration, light intensity, temperature, and relative humidity were all monitored and collected as shown in Figure 7a, 7b, 7c, and 7d respectively. The raw data was filtered for any anomalies or problems encountered during the experiment. The CO_2 gas exchange rate representing the net photosynthesis rate was also monitored as shown in Figure 7e. The net photosynthesis is positive during the light cycle representing the assimilation



(a)



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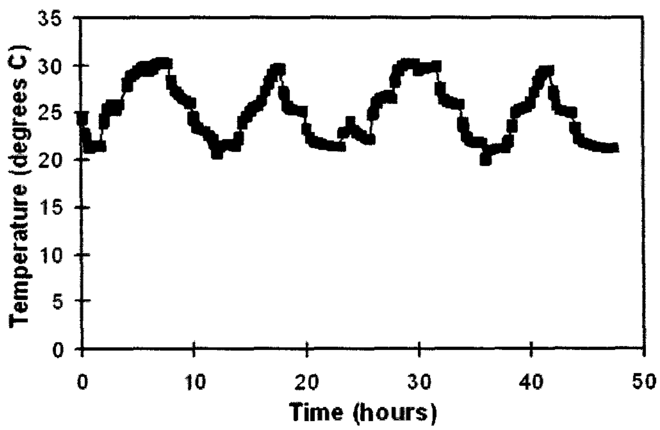

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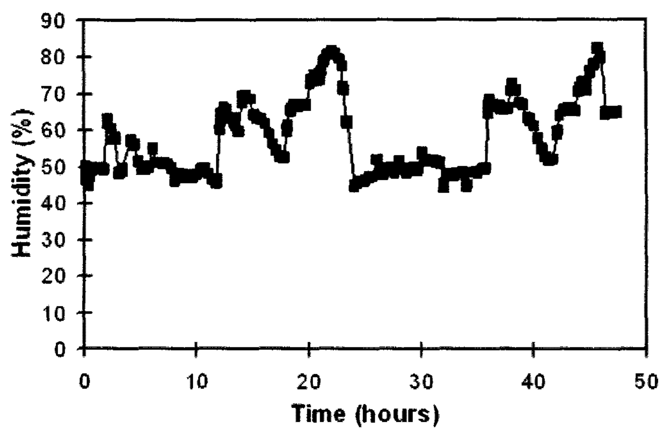
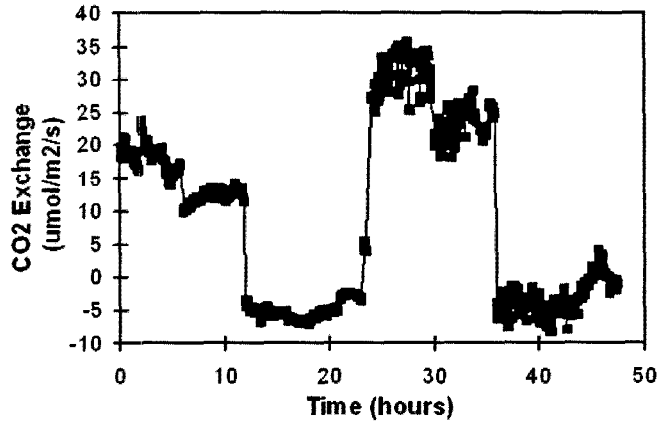


(d)



(e)

Figure 7: Data from soybean crop experiment: (a) CO_2 concentration, (b) light intensity, (c) temperature, (d) relative humidity, (e) net photosynthesis.

process and negative during the dark cycle representing the respiration process.

RESULTS

The data from the soybean experiment was directly used to train the artificial neural network model. The data was split in half with every other data point used for training and the other half used for verification. The neural network architecture, as shown in Figure 3, was trained using a modified error-backpropagation (generalized delta rule) learning algorithm. The neural network was initially trained on basic mathematical (physiology) models of photosynthesis before being trained on the experimental crop data. This initial training establishes a framework and a baseline for the neural network model. The experimental crop data is then used to further expand and refine this model. Error-backpropagation is one of the various methods available to train a neural network architecture.[3,4] It is a gradient descent method to minimize the total squared error of the output computed by the network. The training of the network by backpropagation involves feeding the input patterns through the network, determining the error between the computed results of the output of the network with their target values, and propagating this error value back into the network by simultaneously adjusting all the synaptic weight connections so that next time the resulting outputs for the same input pattern are closer to their targeted values. This process is iterated numerous times until the network converges on the solution of the problem and the associated error at the output is minimized.

The neural network was trained for over 150,000 iterations until the total squared error of the output of the network was less than 0.7. With this training, the artificial neural network was able to learn to approximate the photosynthesis process. The neural network model was simulated with the verification data and the results are shown in Figure 8 where the model predicted results of the photosynthesis rate is overlaid on the experimental data. This demonstrates that the artificial neural network was able to successfully model the photosynthesis process of soybean crops and was able to closely predict the photosynthetic rate under the current environmental conditions.

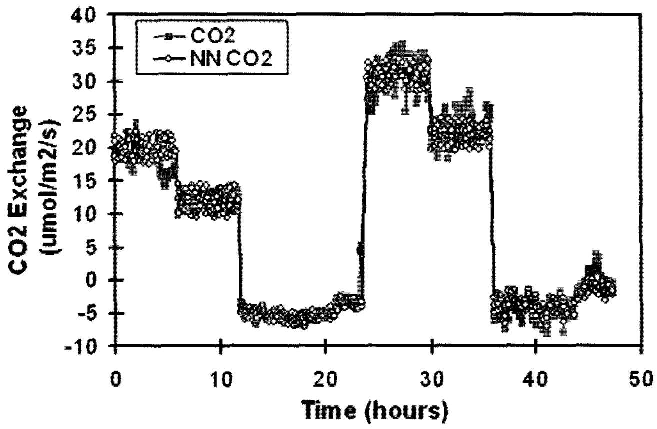


Figure 8: Results of the neural network photosynthesis model.

CONCLUSION AND FUTURE WORK

A 2-layer feedforward neural network architecture was developed to model the assimilation or photosynthesis process for soybean crops under various environmental conditions. The inputs to the neural network model are the crop type, age, and the environmental conditions: carbon dioxide level, light intensity, temperature, and relative humidity of the crop canopy. The neural network model then simulates the net photosynthesis or assimilation rate produced under these conditions.

The neural network soybean model was developed and trained from controlled environment soybean crop experiments conducted at Rutgers University in New Brunswick, New Jersey where dynamic plant responses over a range of environmental conditions were collected. Although this model, trained on this data, can interpolate between these environmental conditions, it is still limited to within these ranges. However, more soybean crop experiments are currently being conducted at Rutgers University.[6] Some of this data will be used to independently validate the existing neural network models. In addition, short-term experiments are being repeated on other stages of crop growth. Long-term experiments lasting 90-days (full life-cycle) with different light intensities and CO_2 levels are being conducted simultaneously. Transpiration data are also being collected in these experiments. The preliminary neural network soybean model can easily be expanded to incorporate the transpiration process and can be augmented with further training of the new crop experiment data. However, the current soybean model demonstrates the potential of how neural networks can model these complex plant processes.

This neural network plant model will lead to the development of a intelligent, autonomous neural network control system that will be able to dynamically manage, control and optimize plant-based life support functions to allow the efficient growth of plants in a bioregenerative life support system.

ACKNOWLEDGMENTS

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